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Automated Demand Response and Storage for Renewable Integration

CEC-500-10-051

California Energy Commission – Public Workshop

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Lawrence Livermore National Laboratory

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Outline

- Project statement, need, and objective
- Analysis framework
  - Wind and solar resource modeling
  - Production simulation modeling
- Valuation results
  - Energy arbitrage and ancillary services
  - Stability
- Summary

Demand response and storage provide opportunities to mitigate variability and uncertainty of renewables

- Grid-scale storage
  - Vary capacity & technology
  - Inform AB2514 storage goals
- Demand response (DR)
  - Fixed capacity by type, hour, and season
  - Derive price at which dispatched
- Analysis
  - Stochastic weather modeling
  - Stochastic optimization methods, multiple timescales

Goal: estimate value that DR and storage can provide.

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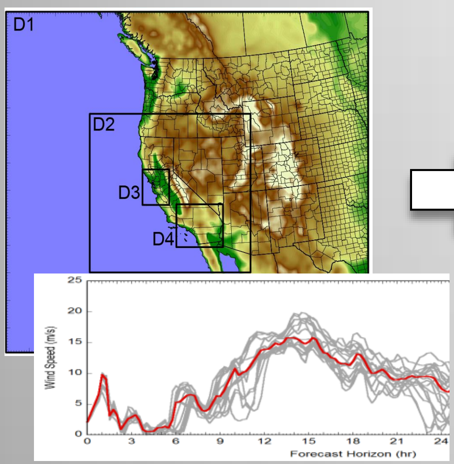
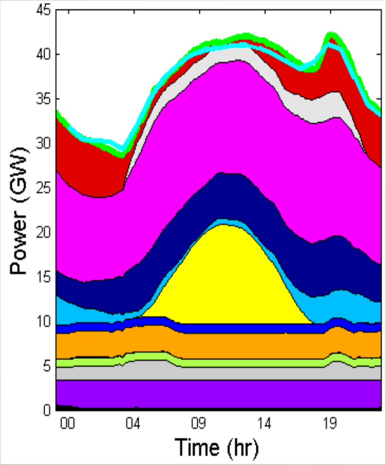
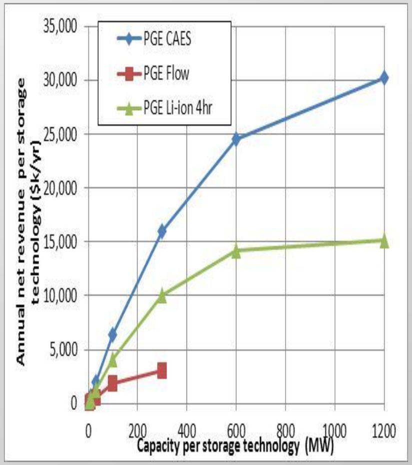
LLNL developed and integrated models to estimate value of storage and demand response under uncertainty



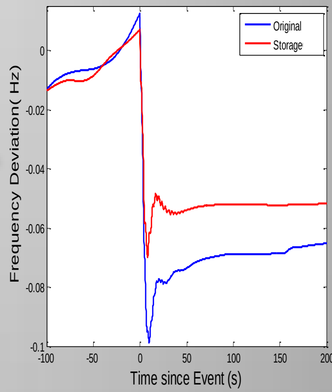
Ensemble weather forecasts with uncertainty (WRF, LLNL code)



Production modeling under uncertainty (PLEXOS, CPLEX)



Supply curves and other detailed analyses



Stability analysis (KERMIT, LLNL code)

Data, models, and high performance computing infrastructure can now be used for other economic studies.

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Model of WECC developed with deterministic Weather Research and Forecasting (WRF) code

- Spatial and temporal resolution
  - 3, 9, 12 km resolution
  - 50 vertical levels
  - 9 million grid cells
  - Output at 15 minute intervals
- WRF calculations
  - Wind speed
  - Solar insolation
    - Sun angle
  - Temperature (load and PV effects)

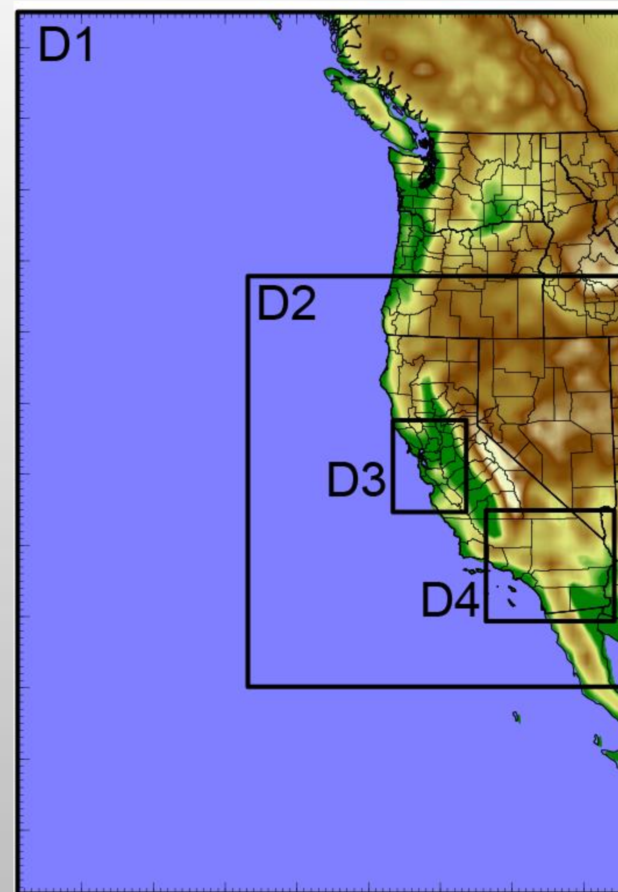
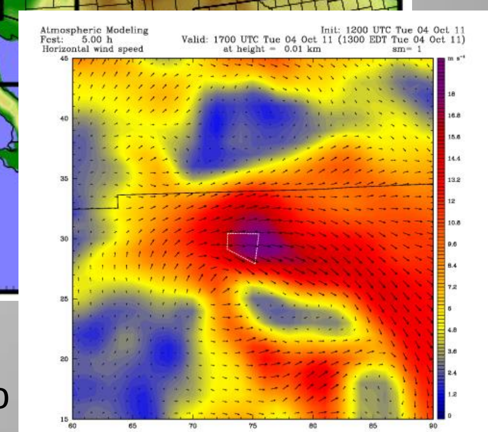


Figure 2-1



WRF wind vectors over San Gorgonio

We represent uncertainty as an ensemble of possible weather trajectories

- First principles models better than statistical for day-ahead uncertainty
- Two sources of uncertainty
  - Initial conditions of atmosphere (e.g., windspeed, temperature, moisture content)
  - Physics submodels (boundary layer, land surface, convection, microphysics, long and short wave radiation)
- Sample parameters to generate ensemble of trajectories
- Forecast started at 16:00 hrs previous day
- Drives load following requirements
- Output time series
  - Wind speed
  - Solar insolation
  - Temperature

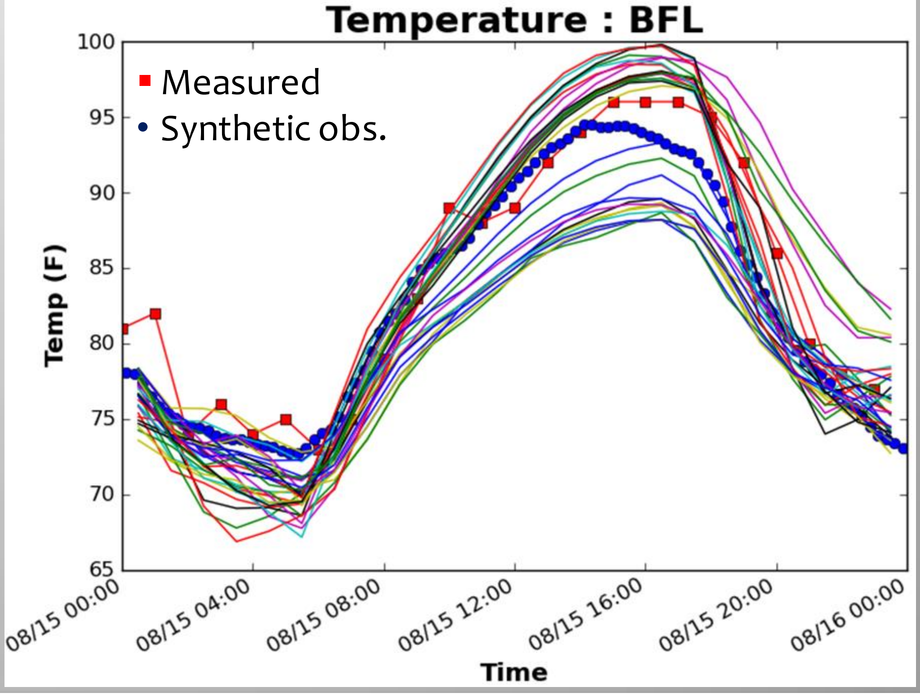
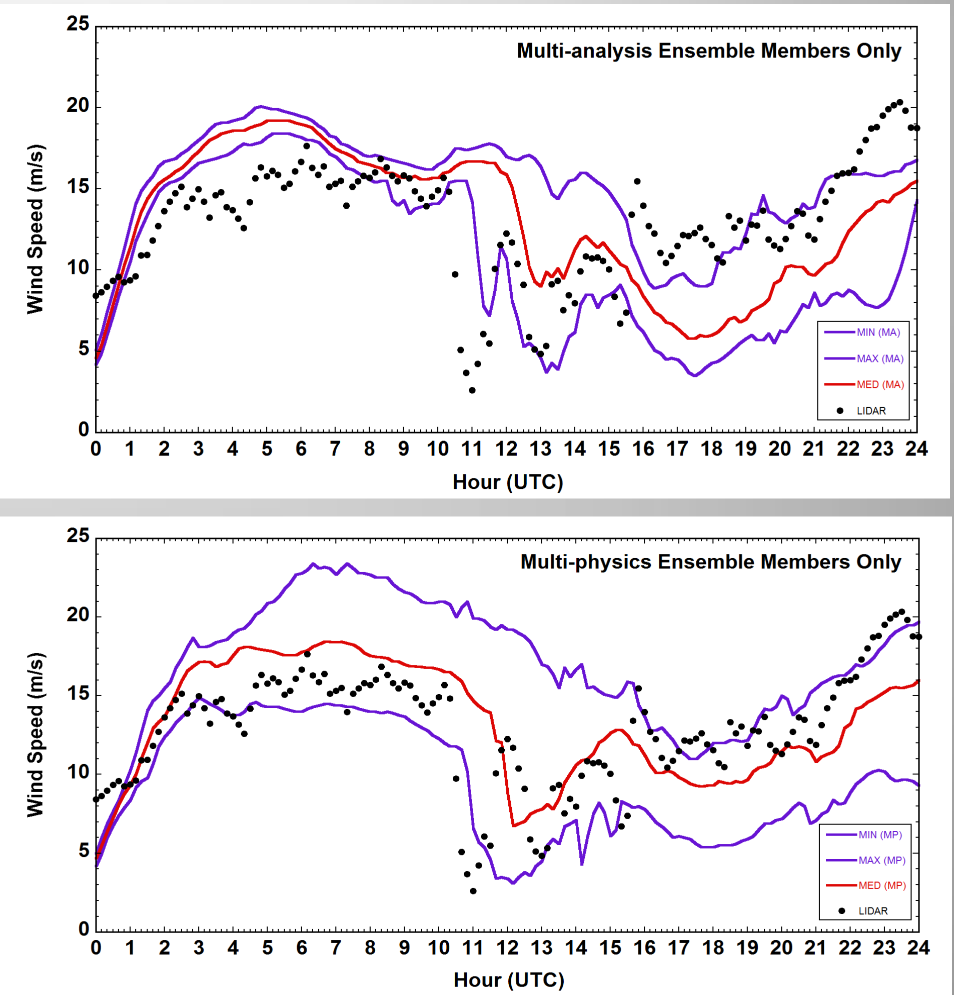


Figure 2-7

Literature and experiments indicate physics submodel variation has more impact than initial conditions

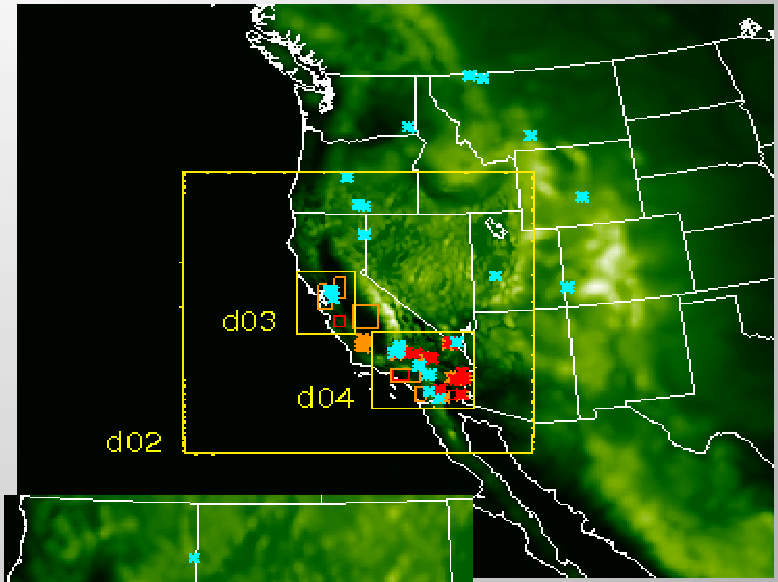
- Modeling and LIDAR measurements at Buena Vista wind park conducted (LLNL funded R&D)
  - Initial condition (multi-analysis) ensemble does not envelop LIDAR measurements
  - Multi-physics ensemble (30) contains most of the measured data
- Additional LLNL-funded R&D to find best physics ensemble (< 30)



Wind and solar generators geo-located in WECC

- Technologies and locations inferred from CAISO 33% renewable study
- Technologies
  - Grid scale solar PV
  - Rooftop solar PV
  - Solar thermal
  - Wind
- Distributed over grid cells in weather model
  - Point locations for wind parks and solar thermal
  - Rooftop solar PV distributed uniformly
  - 5,000 grid cells with renewable generators
- Curtailments allowed but not needed
  - No negative prices observed
  - WECC outside CA dispatched

Figure 2-2



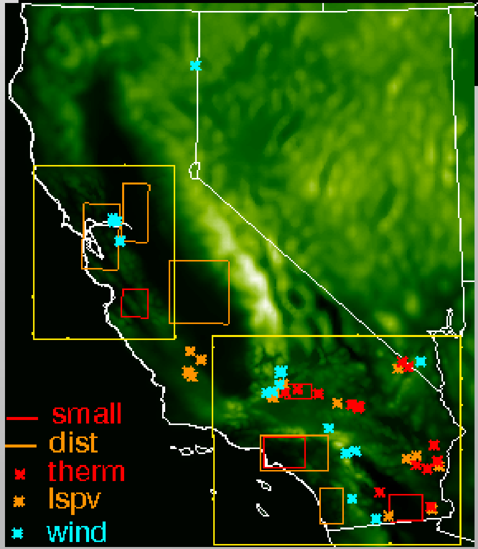
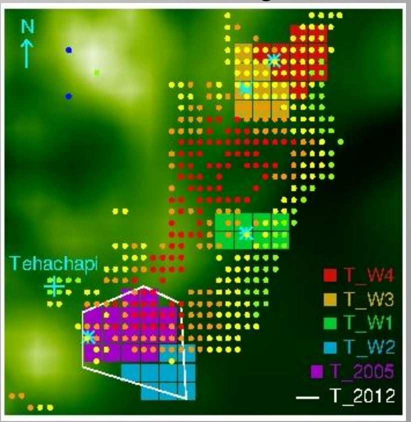


Figure 3-1

Figure 3-6



Power generation computed from WRF output and generator models

- Solar PV power
  - Irradiance on normal surface from WRF
  - Sun-PV angle, fixed and seasonal 1 axis tracking
  - Temperature effects on efficiency
- Vestas wind turbine input-output curve

Figure 3-1

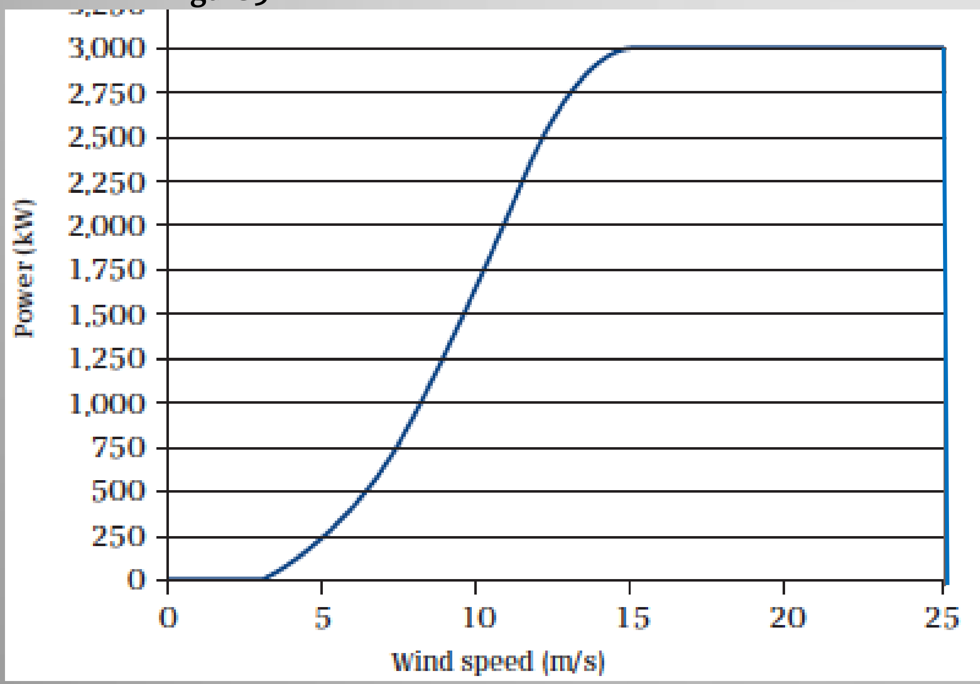


Figure 3-2

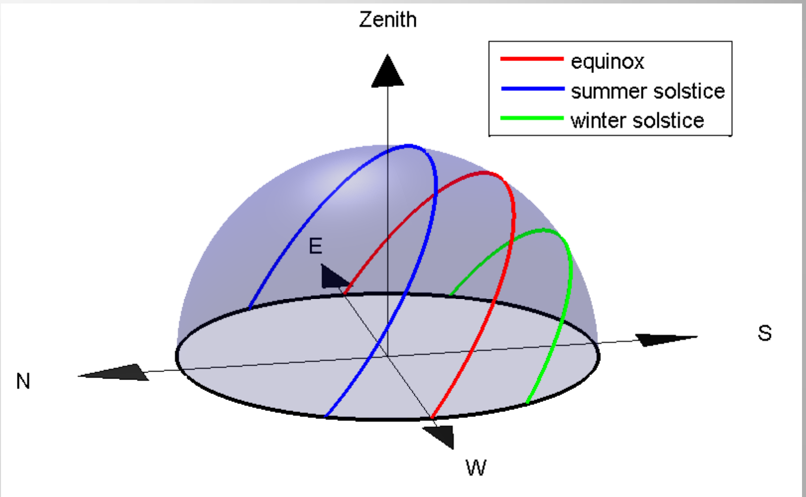
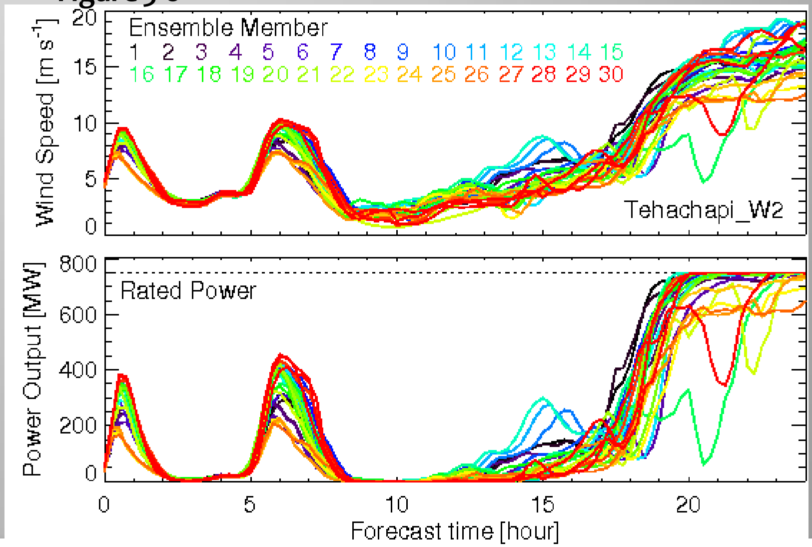


Figure 3-8



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EPRI and California Energy Storage Alliance provided data to analyze storage technologies

Technology	MW	MWh	Capital Cost* ($M)	Specific Capital Cost ($M/MW)	Specific Energy Cost ($M/ MWh)	Var. O&M ($/ MWh)	Plant Life (yrs)	Cycles @ 80% DOD	Cycles @ 5% DOD	Round Trip Eff. (%)
Li-Ion battery (15 min)	2	0.5	2.5	1.25	5	0.25	15	10,000	100,000	83
Li-Ion Battery (4hr)	1	4	3.6	3.6	0.9	0.25	15	5,000		85
Flow Battery (5 hr)	50	250	93	1.86	0.372	0.25	15			65
Flywheel (15 min)	20	5	38	1.9	7.6	0	25	Infinite	Infinite	87
Compressed Air Above Ground (5 hr)	50	250	100	2	0.4	6	35	Infinite	Infinite	70
Compressed Air Below Ground (10 hr)	200	2,000	300	1.5	0.15	6	35	Infinite	Infinite	70

Table E-1

Demand Response Research Center (LBNL) provided DR capacities for each hour of year

- 3 types of DR
  - Economic – bid in day ahead market
  - Load following – 5 minute intervals
  - Regulation – controlled at 4 second intervals
- Price data not provided
- Rebound data not provided
- Late 2012 data, revised

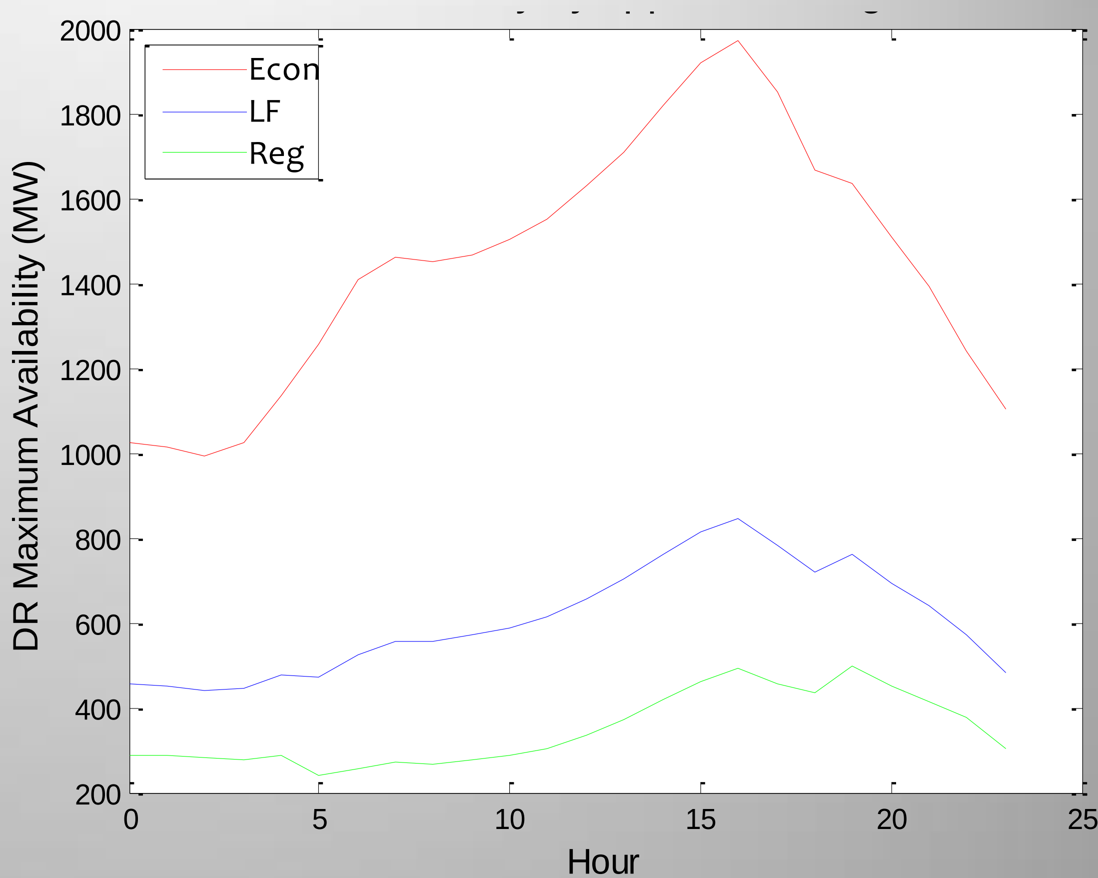

Figure D-2

SCE Sunday Aug. 2, 2020

Up to 2600 MW of DR capacity available for bidding into the day-ahead (DA) markets

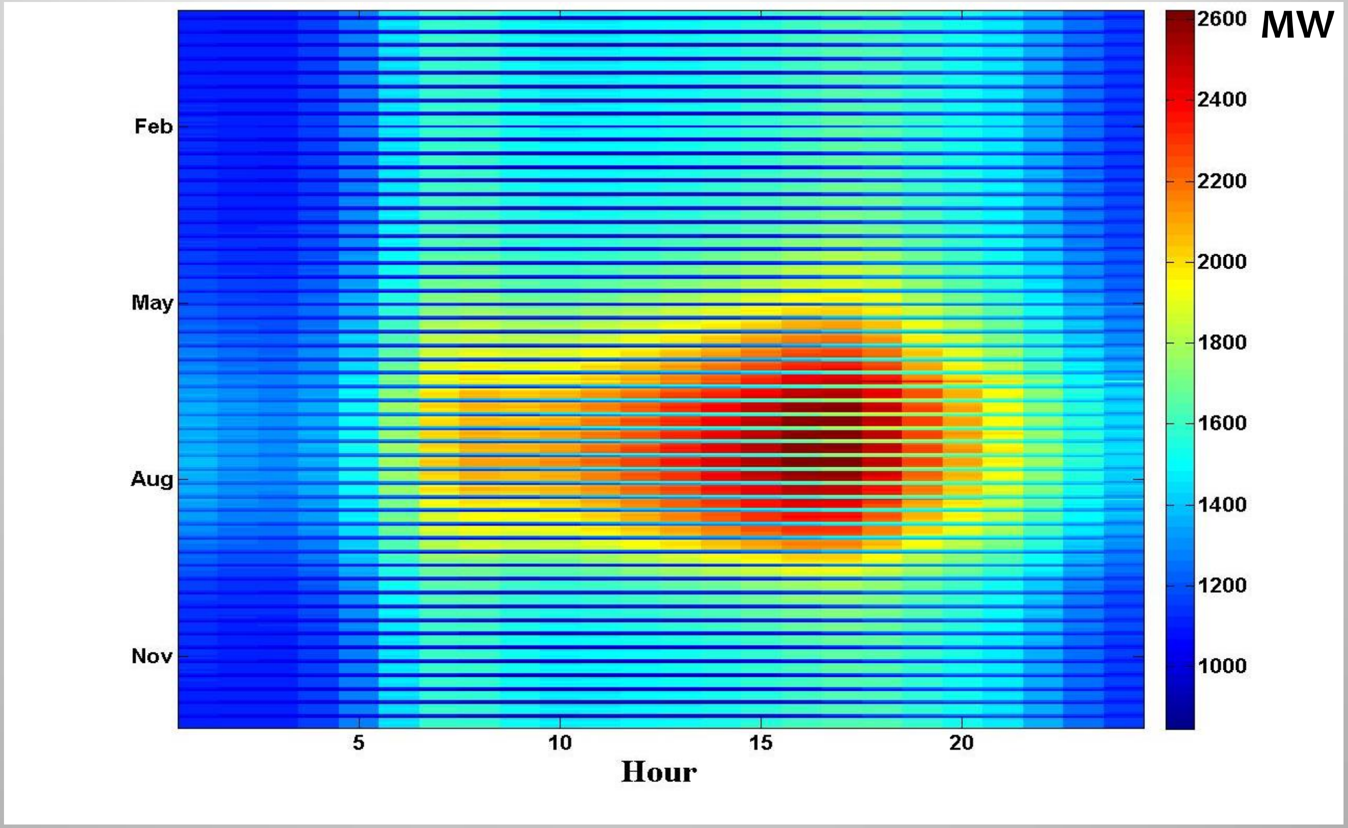

Fig. C-7

Figure D-7

We extended CAISO's hourly, deterministic production simulation model of WECC

- >2000 generators
- 120 transmission corridors, 42 zones
- \$36/ton CO_2 allowances
- Renewables & DR
- Li-ion, flow, air, and flywheel storage
- Two stage optimization
  - Stochastic day ahead unit commitment (hourly time steps)
  - Recommitment of fast-start units and economic dispatch (5 minute time steps)
- Five minute time steps over one year
- Ran model on 23,000 core Linux cluster
  - Simultaneous use of ~2,000 cores
  - LLNL-funded research with IBM to speed up CPLEX optimization code

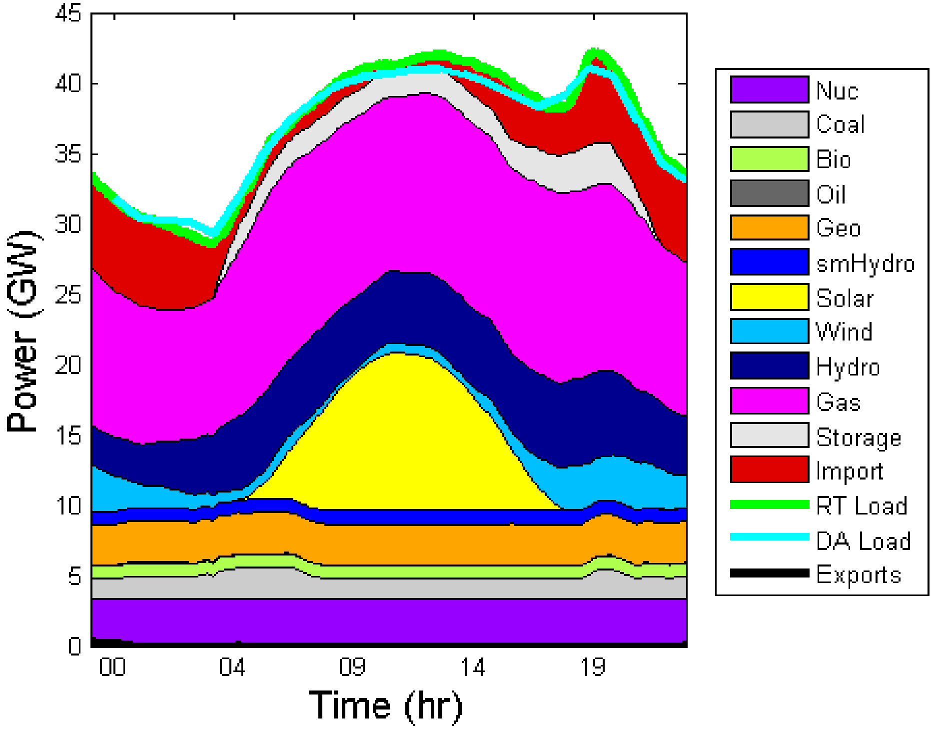

Figure 8-2

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Energy prices for the year exhibit seasonal patterns

- Two high price periods in winter
- Earlier and more prolonged high prices in summer

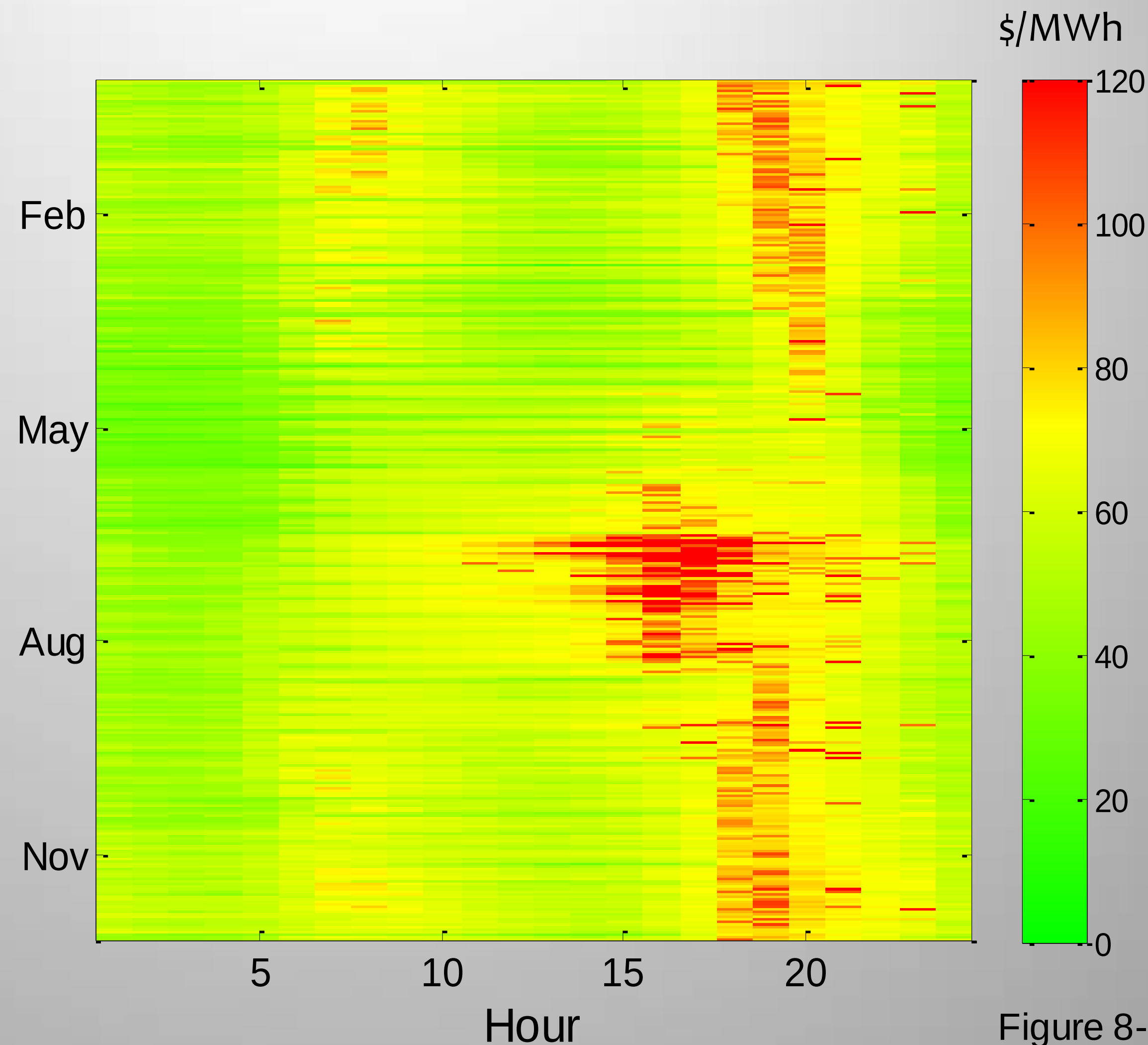


Figure 8-38

Li-ion batteries cycle once in the summer and twice the rest of the year

- Charge (blue) in early morning and mid-afternoon
- Discharge (red) in morning during winter, spring and fall
- Discharge in afternoon all year

Generation and charging for 50 MW of 4 hour Li-ion battery in SCE service territory

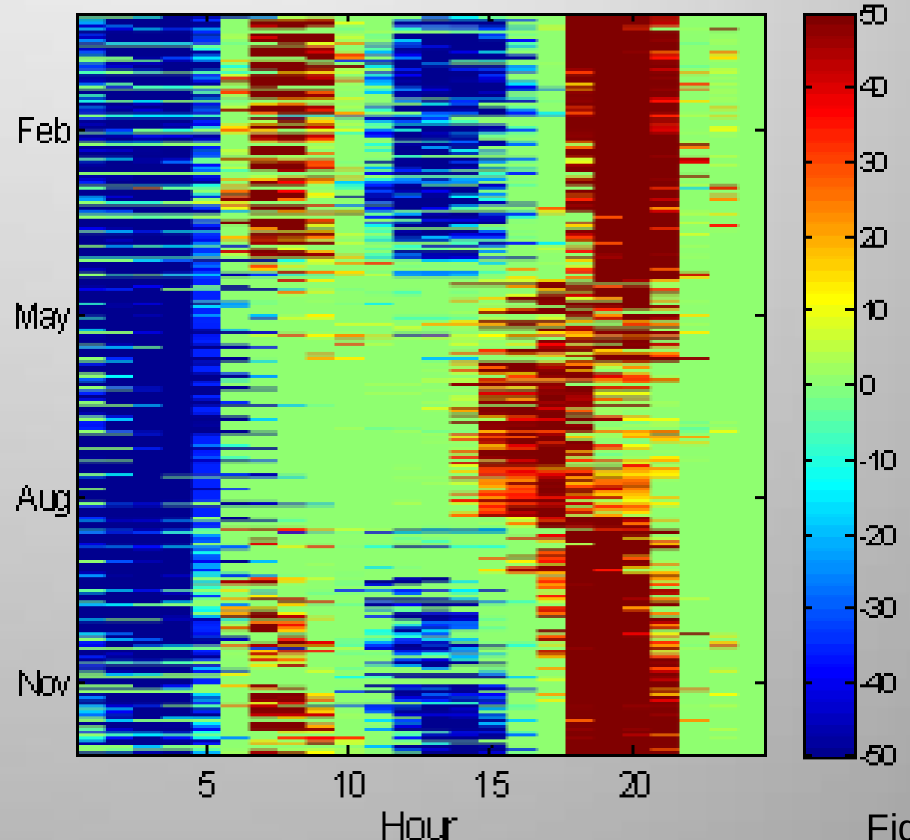


Figure 10-1

Net revenue curves show relative values and diminishing marginal net revenues (3 techs. in PG&E and SCE)

- CAES most cost effective
- Saturation effect at 300 MW per tech. (1800 MW total in CA)
- Flow battery not dispatched when 2400 MW of CAES and Li-ion built

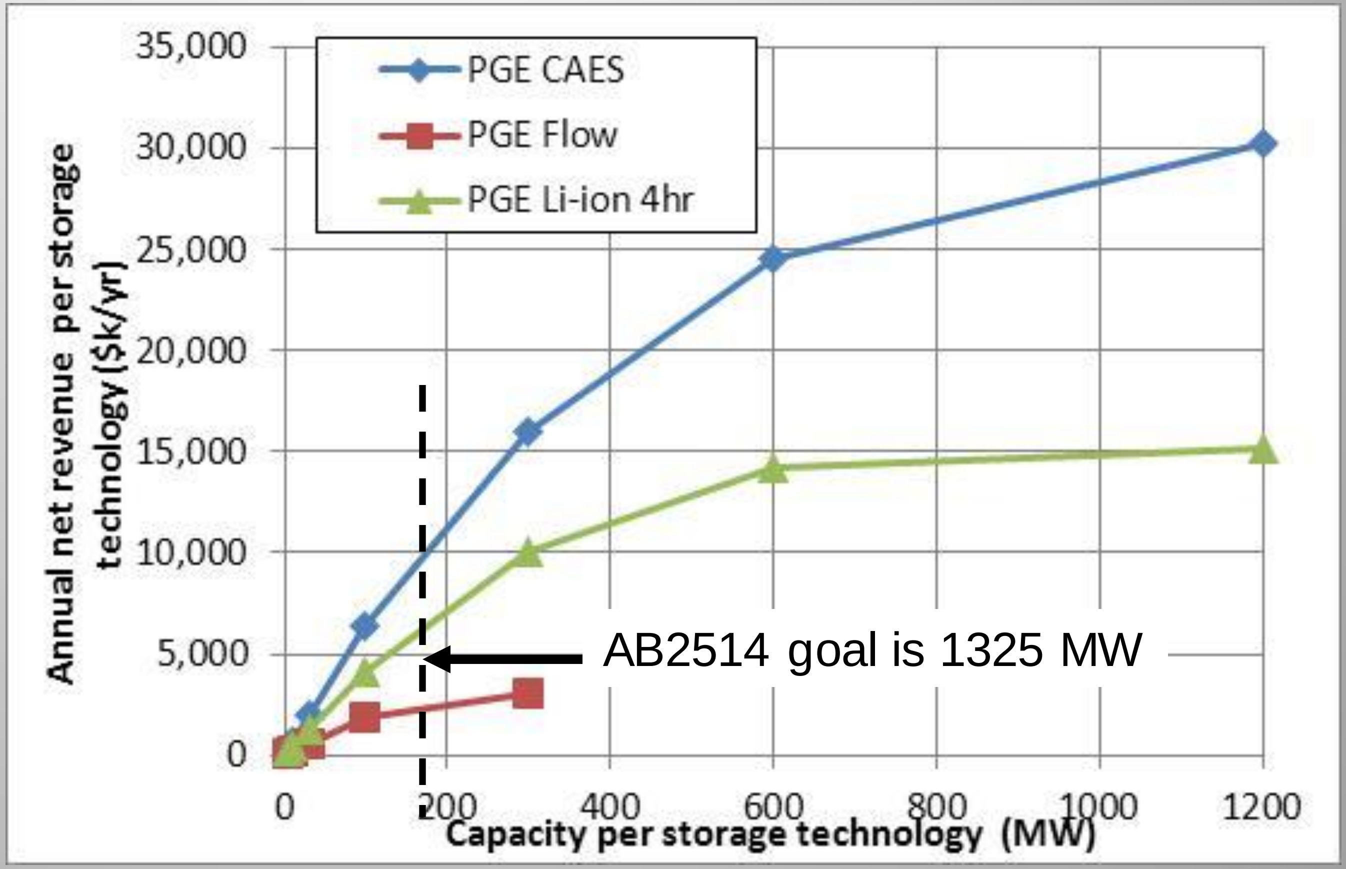


Figure 10-9

Discharge times longer than 3 hours do not offer much additional benefit

- 50 MW per tech., per area (300 MW total)
- Net revenues saturate at about 3 hours

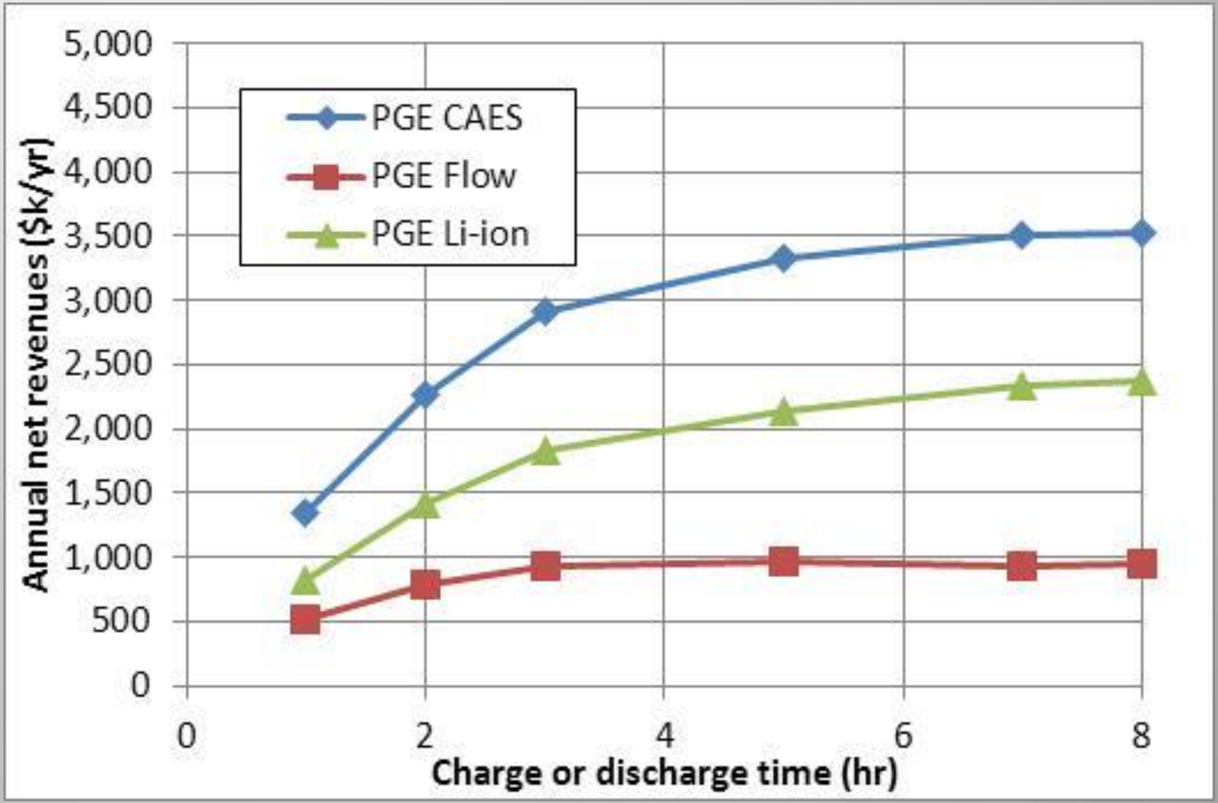


Figure 10-13

Prices for regulation up and down reflect periods of ramping up and down

Regulation up

- High prices at random times throughout the year
- High prices in late afternoon in July

Regulation down

- High prices around midnight

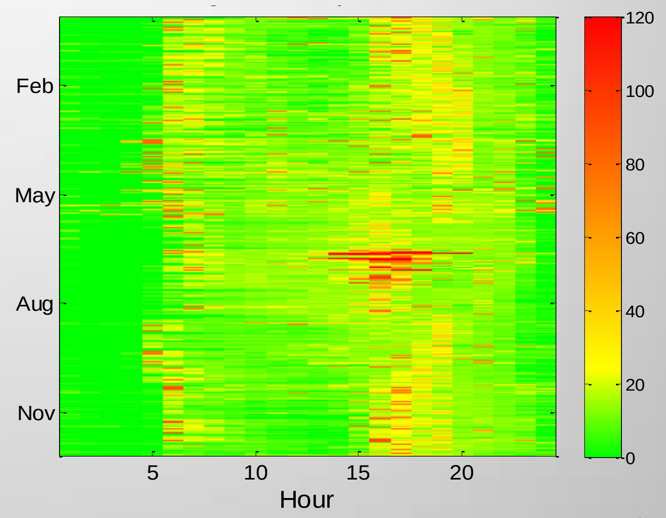


Figure 8-41

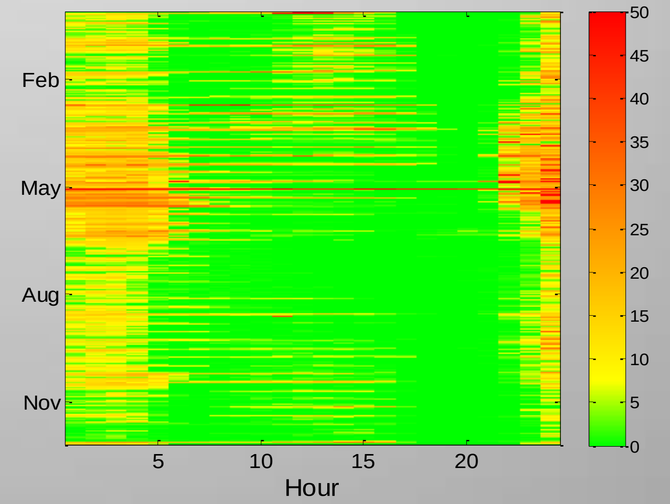
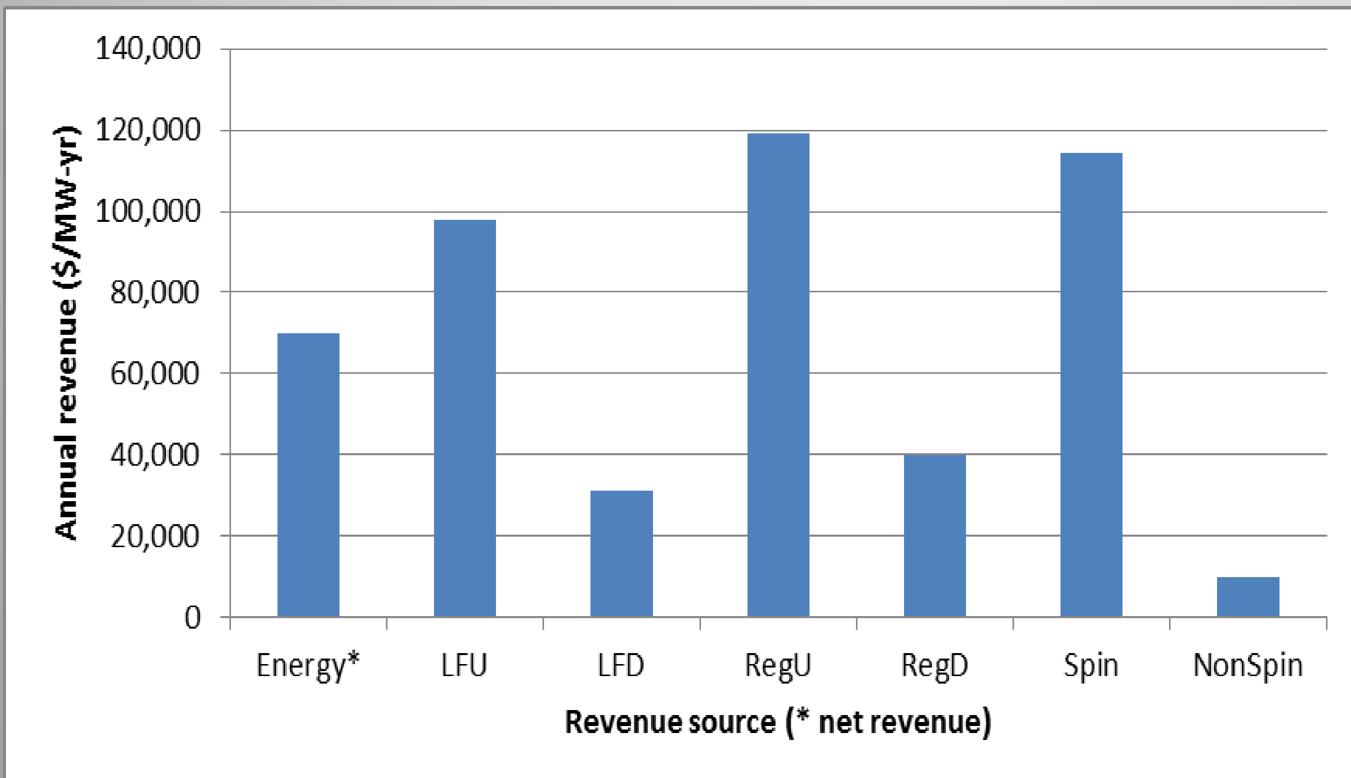


Figure 8-42

Revenue streams from ancillary services could augment energy revenues

- Net energy revenues for energy arbitrage
- Ancillary services prices summed for the year



LFU = load following up
LFD = load following down
RegU = regulation up
RegD = regulation down
Spin = spinning reserve
NonSpin = non-spinning reserve

Fig. 10-19

Energy arbitrage profits currently lower than levelized capital cost by at least a factor of 4 (today)

Table 10-6

Discount rate	15%			Levelized	Profits from
		Capital cost	Plant	capital cost	energy arbitrage
Technology		($/kw)	life (yr)	($/kw-yr)	($/kw-yr)
CAES		2,000	35	302	70
Flow		1,860	15	318	20
Li-ion 4 hr		3,600	15	616	45
Li-ion 15 min.		1,250	15	214	
Comb. turb.		750	15	113	

4x

- Battery cost reductions – possibly 75%
- Ancillary services – $100/kw-yr
- Capacity credit - $113/kw-yr
- CAES at break-even (70+100+113 = 283 ~ 302)
- Li-ion 4 hr profits (45+100+113 = 258 > 154)

Plexos model used to estimate operating cost savings of DR

- **Used model to find prices at which DR would be dispatched**
  - Initial CAISO prices: $1,000, $600, and $136/MWh
  - LLNL-derived prices: $130, $105, and $80/MWh
- **DR for load following** –Savings of 0.7%
  - 0.8% if 2x DR capacity
  - 0.4% if half the DR capacity
- **DR for regulation** – Savings of $31M/yr (0.3%)

Future work: are LLNL-derived prices consistent with capacities provided by DRRC?

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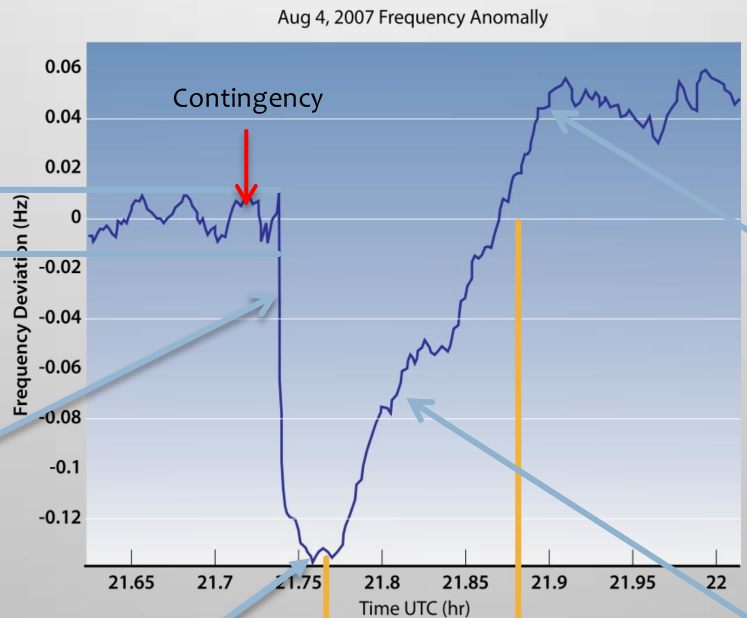
We used DNV-GL code KERMIT and LLNL software to perform regulation and stability analysis

Evaluate a diverse set of system states and contingencies



Frequency stability during normal conditions

Secondary events?

Time to stabilize at minimum/maximum frequency

Recovery time

Overshoot

Impact of renewable variations on recovery

Addition of 200 MW of storage for regulation improves response to contingencies

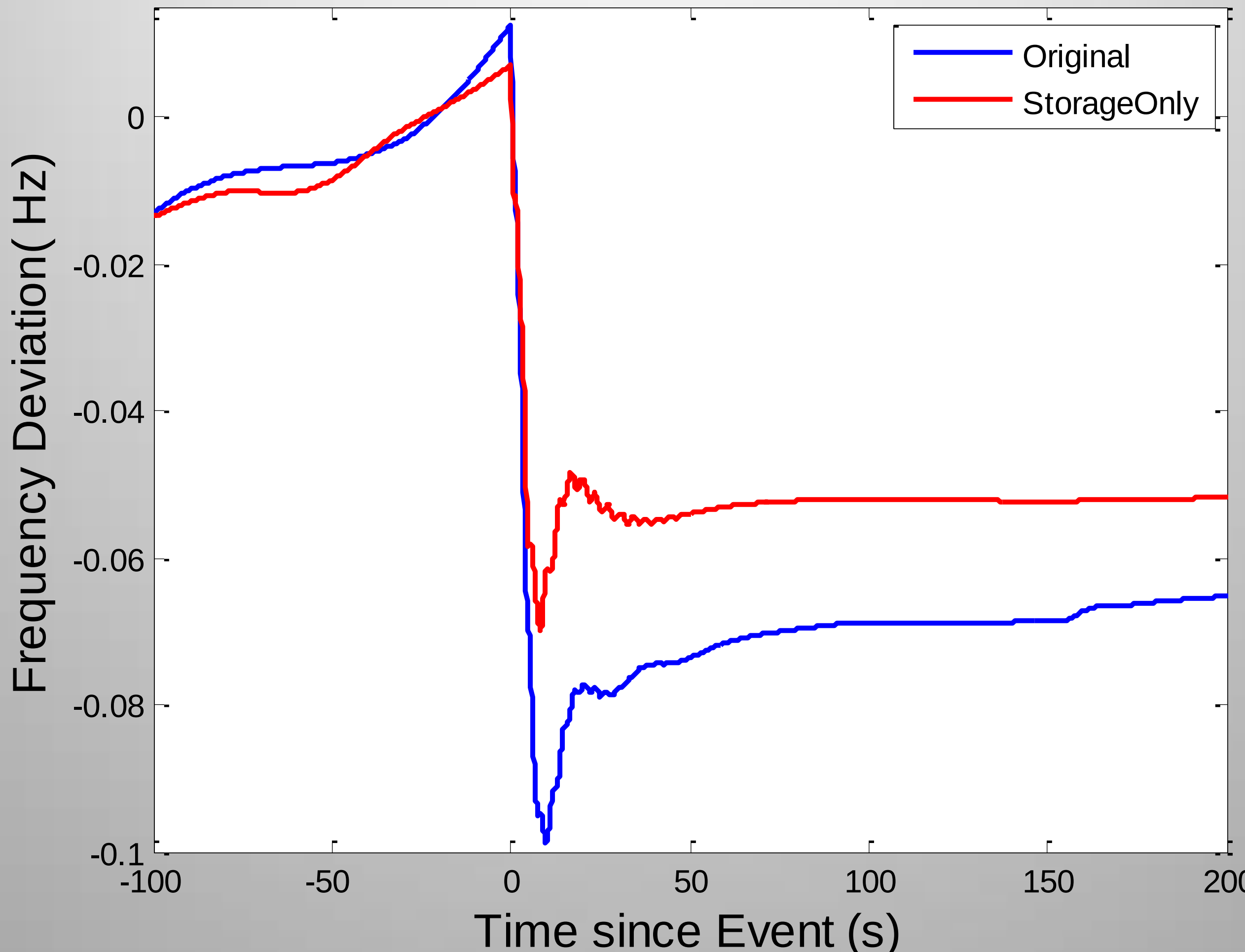


Fig. 11-21

100-200 MW of storage reduces cycling of gas and other units providing regulation

Cycling (mileage)

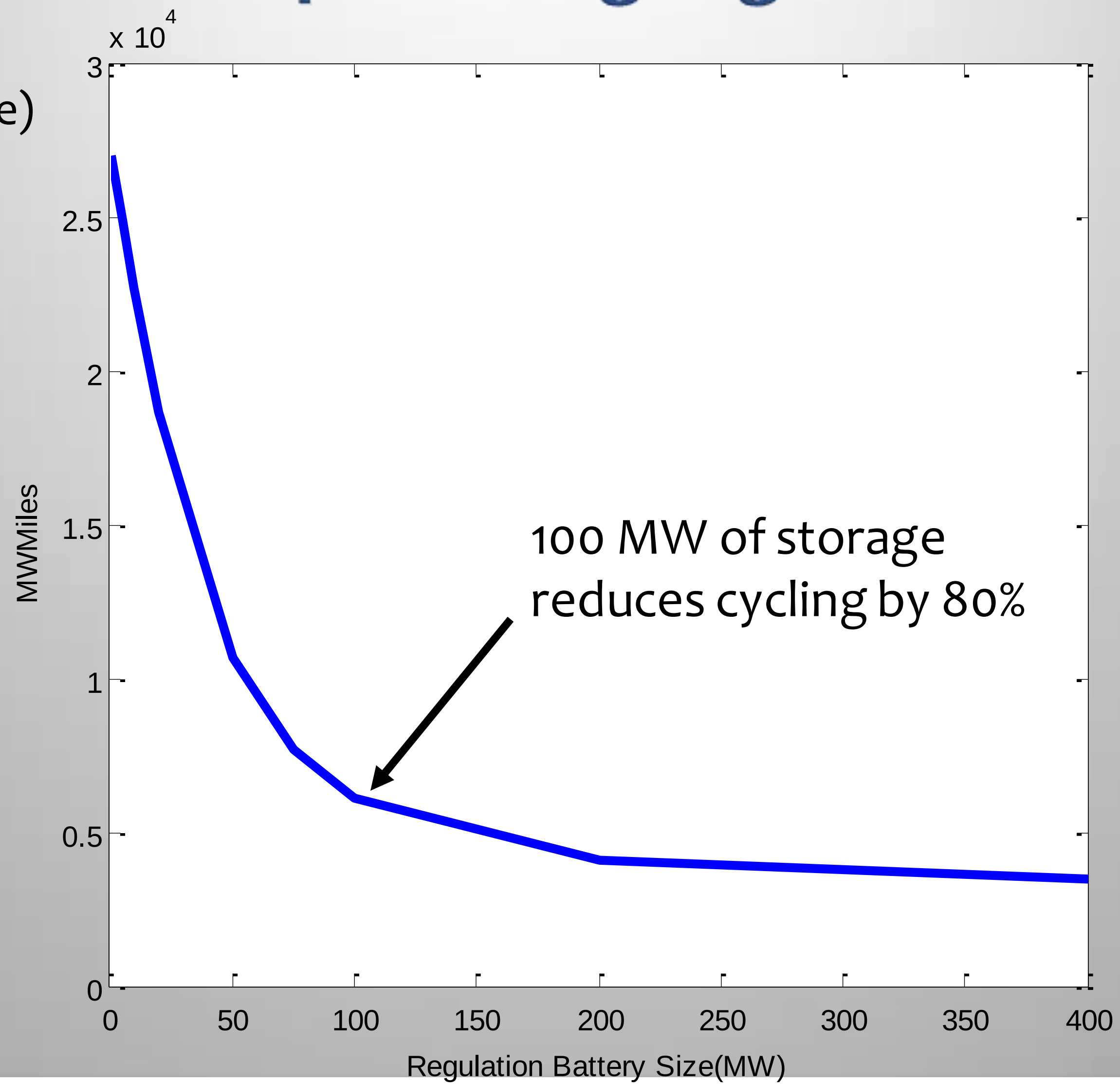


Fig. 11-11

Summary

- **Weather uncertainty** – ensemble forecasting at scale
- **Stochastic optimization** – at scale, 5 minute timesteps
- **Storage power** – Decreasing returns to scale above ~1200 MW
- **Discharge time** – Decreasing returns to scale above ~3 hours
- **Storage economics** – Need AS revenues, avoided capacity credits, and/or reductions in capital costs
- **Demand response** – Save 0.7% of operating costs
- **Stability impacts** – Worse when more renewables on line or light loads
- **Reduction in MW-miles** – 100 MW storage on regulation reduces cycling 85%

We collaborated with other organization and leveraged previous work

Team

- Subcontract California Institute for Energy and Environment
- Subcontract with KEMA Corp.: Kermit software, consulting
- Demand Response Research Center

Collaborators

- CAISO: Data, models, requirements
- National Center for Atmospheric Research: WRF/DART
- EPRI & California Energy Storage Alliance: data

Tools

- IBM: CPLEX optimizer implementation on HPC
- Energy Exemplar: PLEXOS support, implementation on HPC
- NREL: System analysis model, datasets

Questions or comments?